Location Management in Cellular Networks using Soft Computing Algorithms

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LOCATION MANAGEMENT IN CELLULAR NETWORKS USING SOFT COMPUTING ALGORITHMS

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May 2014

Declaration of Authorship

I, **Addanki Prathima**, declare that this thesis titled, 'Location Management in Cellular Networks using Soft Computing Algorithms' and the work presented in it are my own. I confirm that:

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This is to certify that the thesis entitled, **"Location Management in Cellular Networks using Soft Computing Algorithms"** submitted by **Addanki Prathima** in partial fulfilment of the requirements for the award of Master of Technology Degree in **Electrical Engineering** with specialization in **Electronic Systems and Communication** during 2013-2014 at the National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by her under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university / institute for the award of any Degree or Diploma.

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Abstract

The enormous increase in mobile subscribers in recent years has resulted in exploitation of wireless network resources, in particular, the bandwidth available. For the efficient use of the limited available bandwidth and to increase the capacity of the network, frequency re-use concept is adopted in cellular networks which led to increased number of cells in the network. This led to difficulty in finding the location of a mobile user in the network and increase in the signalling cost. Location management deals with keeping track of an active mobile terminal in a specific area while minimizing the cost incurred in finding the mobile terminal. The existing location management is done by grouping the cells based on subscriber density. Location management strategies are based on user mobility and incoming call arrival rate to a mobile terminal, which implies that the location management cost comprises of location update cost and paging cost. Reporting cell planning is an efficient location management scheme wherein few cells in the network as assigned as reporting cells, which take the responsibility of managing the location update and paging procedures in the network. Therefore, the need of the hour is to determine an optimal reporting cell configuration where the location management cost is reduced and thereby maintaining a trade-off between location update and paging cost. The reporting cell discrete optimization problem is solved using genetic algorithm, swarm intelligence technique and differential evolution. A comparative study of these techniques with the algorithms implemented by other researchers is done. It is observed that binary differential evolution outperforms other optimization techniques used for cost optimization. The current work can be extended to dynamic location management to assign and manage reporting cells in real-time implementable fashion.

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Last but not the least, I would like to thank my parents, Satya Rao and Jayanthi, for their unconditional support throughout my life and belief in me.

Signed: ____________________

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Abbreviations

BPSO	**B**inary **P**article **S**warm **O**ptimization
BS	**B**ase **S**tation
DE	**D**ifferential **E**volution
HLR	**H**ome **L**ocation **R**egister
GA	**G**enetic **A**lgorithm
LA	**L**ocation **A**rea
MSC	**M**obile **S**witching **C**enter
MT	**M**obile **T**erminal
RC	**R**eporting **C**ell
RCC	**R**eporting **C**ell **C**onfiguration
RCP	**R**eporting **C**ell **P**lanning
PSTN	**P**ublic **S**witched **T**elephone **N**etwork
VLR	**V**isitor **L**ocation **R**egister

CHAPTER 1

Introduction

1.1 Introduction

Day to day increase in mobile subscribers in recent years has resulted in exploitation of wireless network resources, in particular, the bandwidth available. This is due to the consumption of a large bandwidth by the numerous broadcast signals. For the efficient use of the limited available bandwidth and to increase the capacity of the network, frequency re-use concept is adopted in cellular networks which led to increased number of cells in the network [1]. This made it difficult to keep track of the mobile user in the network and also led to increased signalling cost. Also, the network should provide constant service to the consumers using mobile phones irrespective of the time and current location.

Mobile wireless networks are versatile in nature as they facilitate user mobility. They aim to provide uninterrupted communication at any time and anywhere with a good quality of service and less delay in locating the target mobile terminal (MT)[2]. Every mobile terminal is connected to a cellular network via a wireless link. Mobility in the context of wireless networks is of two types: user mobility and terminal mobility. User mobility refers to the ability of mobile users to make and receive calls, and access other wireless services irrespective of the MT's location. Terminal mobility is the ability of a mobile terminal to access telecommunication services from any location while in motion, and the capability of the network to locate and identify the mobile terminal as it moves within the coverage area. This project concentrates on network mobility which consists of location management in terms of total cost reduction in location update and paging.

Location management is an important issue in wireless cellular networks because wireless devices are free to move, and can change location while connected to the network [3]. Mobile terminals should be able to send and receive calls or data, while maintaining the quality of service. Hence, it is required to keep constant track of the location of a mobile terminal with a network. In these circumstances, location management seems to be a problem because mobile terminals change their location while being connected to a specific network. Location management strategies are based on user movement rate and incoming call arrival rate to a mobile terminal.

1.2 Literature Review

Location Management aims at reducing the overhead required in finding the location of a mobile terminal in a cellular network and establishing a tradeoff between location update and paging cost. A research survey on location management in cellular networks was presented in [4]. The cost and resource availability issues in cellular networks were solved using location management schemes. Work has been done in location area planning [5], wherein cells are grouped in an optimized way so that the location management cost is reduced. Many studies have been reported in optimal location area planning using evolutionary algorithms [6]. In addition, grouping strategies have been presented by researchers for efficient location area planning [7].

Another approach to location management is Reporting Cell Planning (RCP), proposed by Bar-Noy and Kessler in [8]. In this method, few cells are assigned as reporting cells and the cost function depends on these reporting cells. A mathematical model for the RCP problem has been given in this paper. Optimum reporting cell configuration is determined corresponding to reduced location management cost. Few algorithms have been implemented for the same. Table 1.1 shows the optimization algorithms implemented for RCP so far, their contributions and limitations.

TABLE 1.1: Literature Review

Algorithm	Year	Contributions	Limitations
Genetic Algorithm, Ant Colony Algorithm, Tabu Search [9]	2003	Addressed the use of GA, ACO and TS in reporting cell problem.	Implemented only for a small networks. GA selection is not efficient.
Simulated Annealing [10]	2007	New approach to solve location area planning is proposed.	Inefficient for discrete optimization. Implemented for 16 cell network only.
Differential Evolution [11]	2011	DE has been efficiently implemented for location area and reporting cell problem.	Continuous form of DE is used for discrete optimization. Not suitable for large networks.

1.3 Motivation

Large number of mobile subscribers and increased number of cells for efficient bandwidth use in a wireless network area, made it difficult to find the location of a mobile terminal. The signalling cost involved in finding the mobile subscriber's location is directly related to the movement rate and the call arrival rate of the mobile terminal. This cost called as the location management cost can be minimized using optimization algorithms . The existing location management technique is location area planning [12], where cells in a network are grouped continuously depending on the subscriber density. Reporting cell planning is another location management strategy. This method can be equally efficient and practically feasible provided the cost is minimized. It has been already implemented using classic evolutionary algorithms. But in recent years, many algorithms have been proposed which are much efficient than the traditional algorithms. Reporting cell planning optimized with these algorithms holds good promise to location management in cellular networks.

1.4 Objective

The objective of the thesis are:

- To study the concept of location management in cellular networks.
- To study reporting cell planning method in location management.
- Implement and analyse various soft computing algorithms to minimize location management cost.
- Comparative study of the optimization techniques used and the results obtained.

1.5 Contribution of the Thesis

The following are the salient contributions of the thesis:

- Reporting cell planning approach to location management is studied.
- Various optimization algorithms have been studied, analysed and implemented for reducing location management cost.
- A comparative study of the optimization techniques and detailed analysis of the results obtained is presented.

1.6 Thesis Organization

- Chapter 1 **Introduction** This chapter gives the background theory of the project. It explains the motivation to the project and the objectives to be achieved. It presents an overall introduction to the project.
- Chapter 2 **Location Management** Fundamentals of cellular concepts, GSM system architecture, frequency reuse are explained. Location management concepts are explained. Reporting Cell planning scheme is introduced and illustrated. Problem statement is defined.
- Chapter 3 **Optimization Algorithms** Genetic algorithm, binary particle swarm optimization and binary differential evolution concepts are illustrated in detail. An outline of the algorithms is presented. Implementation of the algorithms with respect to the problem statement is discussed and the corresponding simulation results are shown.
- Chapter 4 **Comparative Study of the Implementation Strategies** A comparative study of the results obtained using different algorithms is presented and analysed.
- Chapter 5 **Conclusions and Future Scope**

CHAPTER 2

Location Management

2.1 Introduction

Wireless Communication has become an essential part of daily life. There is no world without wireless communication. Specifically, confining our focus to mobile communication, mobile phones have become an inevitable part of man. With the invent of cellular communication, the world has become so small and is connected to every nook and corner. The modern day technology has made improvised cellular communication in terms of portability, quality of service, reliability, affordability and various services offered to users [13]. Thus, wireless cellular networks have been adapted to mobility. There is a rapid exponential growth in cellular communication since years and will continue to be so in the future. This growth in consumer-based communication systems is directly related to radio spectrum exploitation. This is explained in detail in the subsections below.

2.2 Cellular Concepts

2.2.1 Cell

Cell is a basic geographical unit of a wireless network area. Earlier, mobile systems were designed in such a way that a single high power transmitter mounted on a tall structure could achieve a large area. But, due to the increasing number of mobile subscribers and increase in the demand for mobile services, this design resulted in interference and could not allocate the limited spectrum in a large coverage area. Hence, the cellular concept is introduced. The geographical area is divided into number of hexagonal units (theoretically) called as cells. This solved the problem of spectral congestion and catered to the increased user capacity. Instead of using a single transmitter of high power, many low power transmitters are set up in the given cellular area, called as Base Stations (BS). Base station antennas are designed to achieve a desired coverage area i.e. limited to the boundaries of the cell, as shown in Fig 2.1. In short, cells are base transceiver stations (BTS) over geographical areas represented as hexagons, which area capable of transmitting and receiving radio signals.

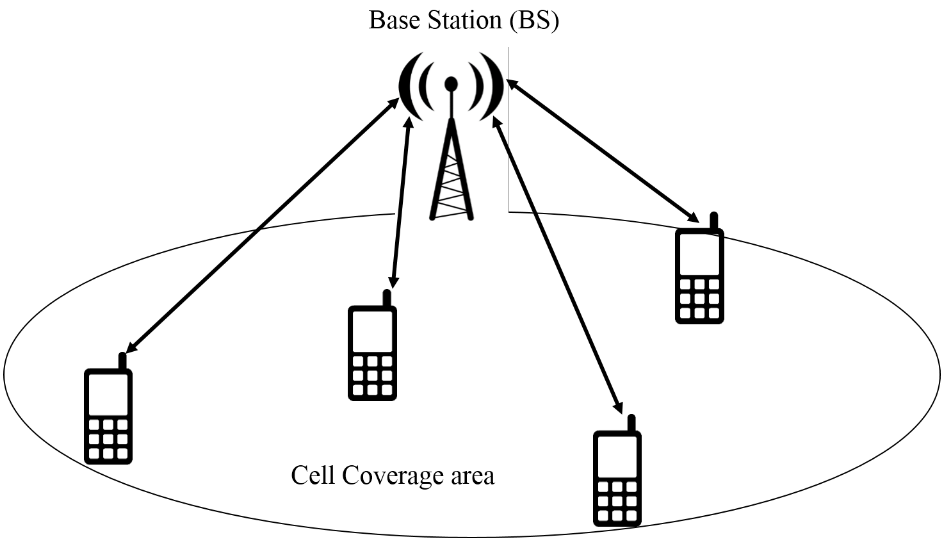


FIGURE 2.1: Cell Coverage Area

2.2.2 Frequency Reuse

Radio frequency spectrum is the range frequencies over which the communication signal travel. Spectrum is a limited natural wireless resource which needs to be used efficiently and economically such that all the consumers get equal access for different wireless communication services. A cellular network can accommodate the limited spectrum to the huge mobile subscriber density, only if the frequencies are reused in the network area. Thus, the concept of frequency re-use is introduced in cellular communication. Same communication channels are used within cells located at different positions separated by a specific distance in the network area. It is also ensured that no interference occurs due to frequency re-use. Cell using the same channels are called as co-channel cells. Separation between co-channel cells is far enough so that co-channel interference is maintained below the acceptable level.

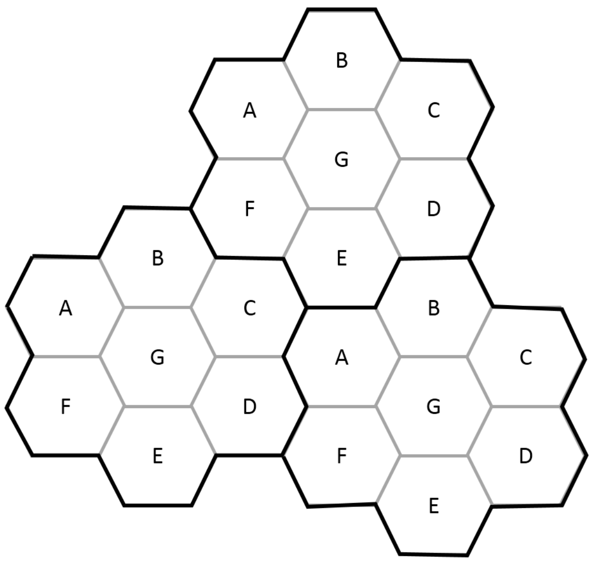


FIGURE 2.2: Frequency Reuse

As seen in Fig 2.2, cells are grouped in clusters of seven and each of the seven cells use different frequency channels. Like named cells in different clusters use the same frequency channels.

As per the recent statistical information, the total number of mobile subscribers in India is 929 million and it is increasing at an annual rate of 40%. International Telecommunication Union (ITU) allocates spectrum bands to various countries. In India, GSM mobile system is primarily followed, which works in the 900/1800 MHz bands. CDMA technology works in 800MHz frequency band.

2.2.3 GSM

Global System for Mobile communications (GSM) is the technology which supports transmitting and receiving of mobile voice and data services. In India, GSM operates in 900MHz and 1800MHz band. GSM consists of two major building blocks: Radio equipment and Core Equipment. Radio equipment is that which provides the subscriber, access to GSM network and services. Core Equipment consists of databases to keep a record of subscriber data, like Home Location Register (HLR) and Visitor Location Register (VLR) which are discussed later. It also performs functions like call handling, billing and other important functions.

The primary unit of GSM is a cell which is defined by a base transceiver station (BTS). BTS transmits and receives radio frequency signals within a defined range thus providing coverage in a confined area. A mobile station communicates with another mobile station via a base station. Routing a call to a mobile station is a not an easy task. For routing an incoming call to the mobile terminal, the network first needs to know the MSC and the cell (i.e. BS) in which the mobile station is currently located. GSM network primarily consists of four subsystems which are explained below.

1. Mobile Station/Terminal (MS/MT)

2. Base Station Subsystem (BSS)

3. Network Switching Subsystem (NSS)

4. Operation and Support Subsystem (OSS)

Mobile Station/Terminal (MS/MT) MT comprises of GSM portable Handset and a SIM card (Subscriber Identity Module). This Mobile Equipment (ME) has a unique IMEI (International Mobile Equipment Identity) number. MT starts functioning once SIM (Subscriber Identity Module) card is inserted in the handset. SIM card also has a similar IMSI number (International Mobile Subscriber Identity). The primary function of MS is to transmit and receive voice and data over the air interface of the GSM system. MT performs various signal processing functions on the transmitted signals, like encoding, digitizing, error protecting, encryption and modulation. Also, it performs inverse signal processing functions on the signals received from the BTS.

A mobile station communicates with another mobile station via a base station. Routing a call to a mobile station is a not an easy task. For routing an incoming call to the mobile terminal, the network first needs to know the MSC and the cell (i.e. BS) in which the mobile station is currently located. The task of finding the current residing cell of a mobile terminal is dealt by location management. MT constantly informs the GSM network of its location during both national and international roaming, even when it is inactive. This facilitates the system to page it, in case of incoming calls/SMSs.

Base Station Subsystem (BSS) The BSS is a set of equipment, namely base transceiver station (BTS) and base station controlller (BSC), responsible for communicating with MTs in a certain network area. A BTS comprises of radio transmission and reception devices, including antennas and all the signal processing units. BTSs have number of GSM radio frequencies. These radio frequencies support voice and data communication between MS and BTS. More are the number of GSM frequencies supported in a BTS, greater is the traffic handling capacity of the BTS. BSC is the only intelligent unit in BSS. Number of BTS's are connected to a BSC as seen in Fig 2.3. It essentially controls the radio functions of GSM system.

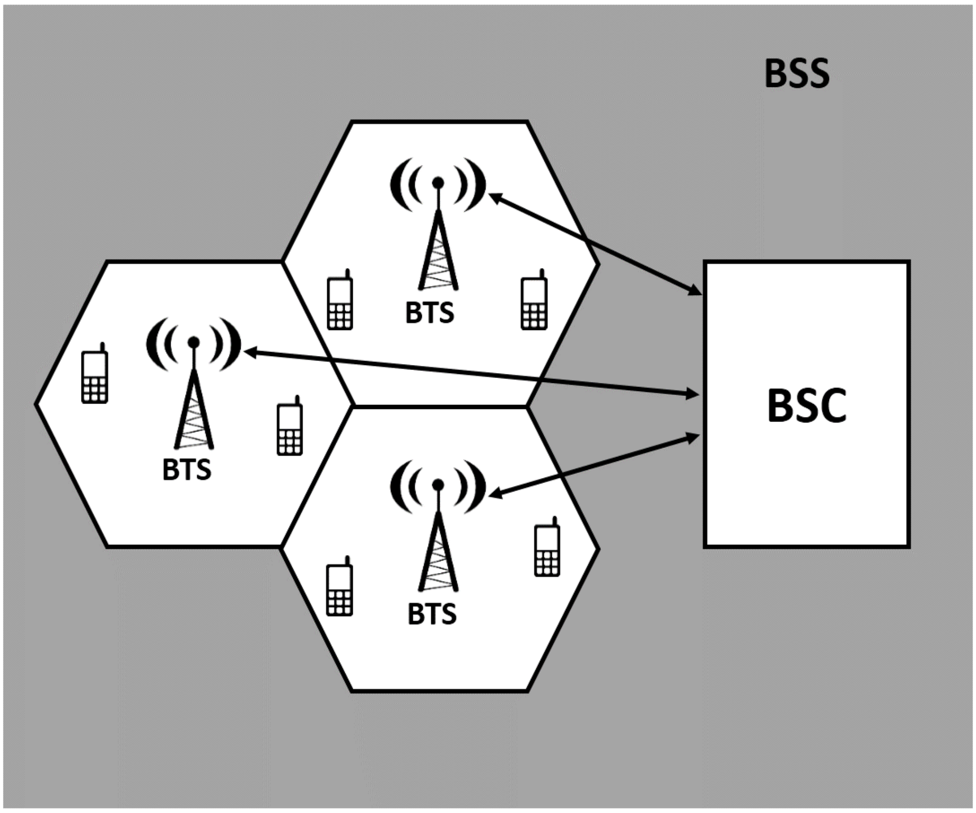


FIGURE 2.3: Base Station Subsystem

Network Switching Subsystem (NSS) The NSS (Network Switching Subsystem) consists of main switch (Exchange) as well as databases required for subscriber data and mobility management. The MSC is the main unit of NSS. It is the switch or exchange for Mobile Network which does the call handling, routing of calls, etc. MSC is also connected to other MSCs of same Location Service Area (LSA) to support mobile calls within same LSA. Similarly, the MSC is also connected to MSCs/Exchanges of other networks like Landline Exchanges and MSCs of other operators/ LSAs to support the call routing to and from other networks. NSS also includes some databases to keep the data of subscribers and their locations. The Home Location Register (HLR) is the main database of GSM system. At the time of a new GSM connection, on activation of services the subscriber data is created in HLR. HLR is the permanent data of all the subscribers of an LSA. There is one HLR in an LSA. Apart from permanent database a temporary database of the subscribers is also maintained in the form of a VLR (Visitor Location Register). Each MSC has a VLR. AuC (Authentication Centre) is another database of NSS to be used to authenticate a SIM (subscriber) in to the network. A subscriber is allowed to access the network after it is authenticated in AuC. EIR is another database that stores the IMEI (International Mobile Equipment Identity) numbers of all registered mobile terminal units. The block diagram of NSS is shown in Fig 2.4

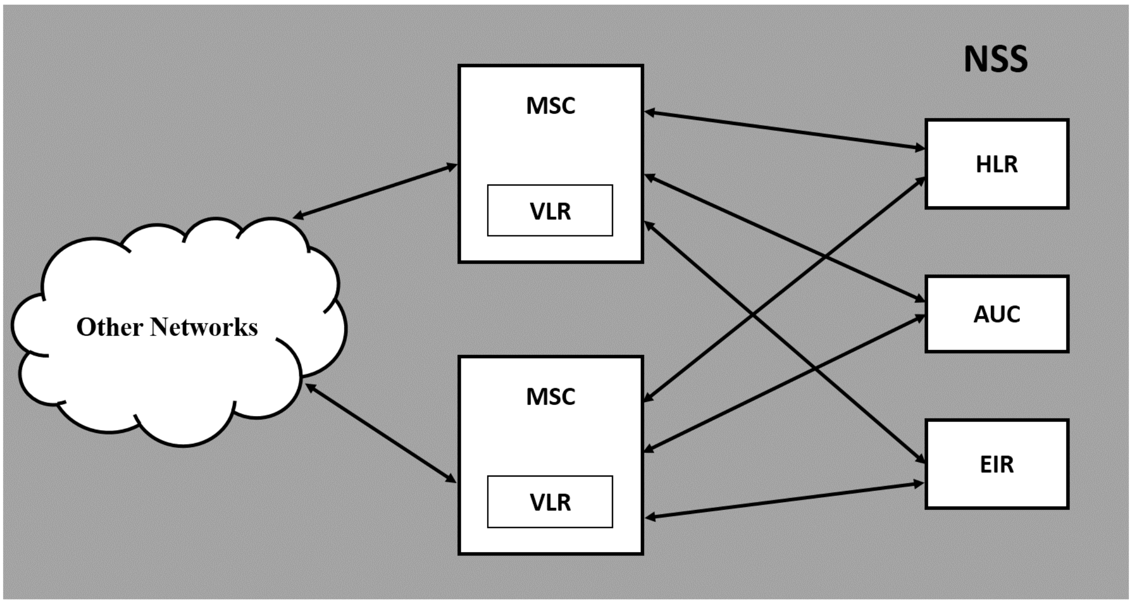


FIGURE 2.4: Network Switching Subsystem

Operation and Support Subsystem (OSS) The OSS is a server used to monitor the network performance. The OSS is connected to all the BSCs and MSCs in the network of an LSA in a LAN/ WAN. An OMC (Operation and Maintenance Centre) is established through OSS which monitors the network round the clock. OSS provides fault management where alarms of network entities are monitored so that corrective action may be taken. OSS also provides network reports which may be used to analyse the network performance. As the OSS is connected to all the network elements, it is also used to control/configure the network entities. The OSS is connected to BSC and MSC as shown in Fig 2.5.

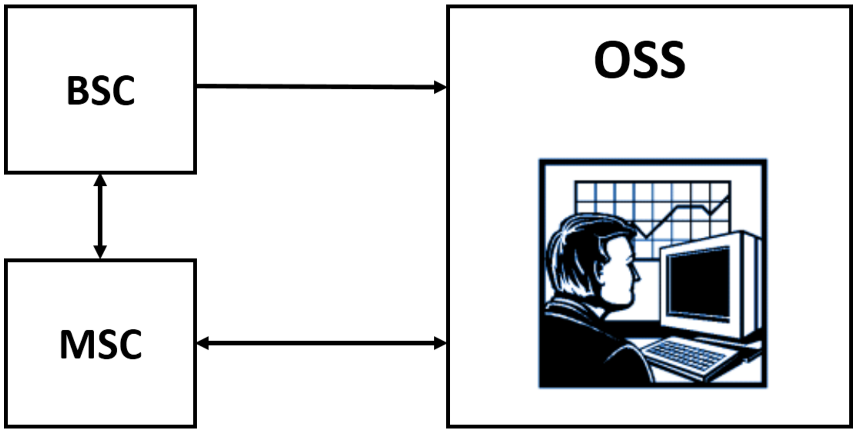


FIGURE 2.5: Operation and Support Subsystem

2.3 Location Management

Location management deals with keeping track of an active mobile terminal within the cellular network. A certain amount of cost is incurred on finding the location of a user, as they move freely with a location area. This cost is known as location management cost. It is directly proportional to the movement frequency of a mobile terminal within a given area and the number of call arrivals to that mobile terminal. Management of network resources or developing strategies to reduce this cost is known as location management [14]. There are two basic operations involved with location management i.e. Location Update and Paging.

2.3.1 Location Update

Location Update is necessary to keep track of the mobile user in the network coverage area. It is performed by the mobile terminal. Whenever a mobile user moves from one cell to another cell in a certain coverage area, the mobile terminal automatically sends a location update request signal to the MSC [15]. Thus, the mobile location is updated to the current residing cell and thereafter all the call procedures are carried out by the current residing cell base station until the mobile moves to a new cell.

2.3.2 Paging

When there is an incoming call to a mobile user, the MSC routes the call to the base station in which the mobile terminal is currently residing. The base station then sends a broadcast signal to all the mobile terminals within its coverage area and routes the call to that mobile terminal which responds to the broadcast signal. Thus, the call is set-up between the two mobile terminals. This phenomena is of broadcasting a signal to the mobile terminals within the range of the base station is known as Paging.

2.4 Reporting Cell Planning

2.4.1 Introduction to Reporting Cell Planning

Reporting Cell Planning(RCP) is one approach to Location Management. In RCP, few cells in the cellular network are assigned as reporting cells and the cells other than reporting cells (RCs) are non-reporting cells. This approach to location management was proposed in 1993 by Bar-Noy and Keller. Reporting cells can be adjacent to each other sharing a boundary or scattered in a specified coverage area.

Location update is performed whenever a mobile terminal enters a reporting cell. Next location update is done only when the mobile terminal enters or crosses a new reporting cell. During call arrival to a mobile terminal, paging is restricted to the last updated RC where the MT's location update has been last performed and to its neighbouring non reporting cells. In simple terms, we can

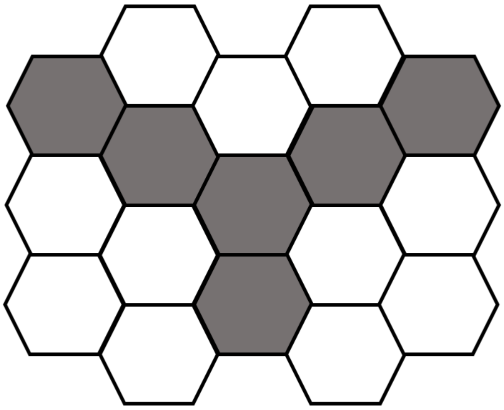


FIGURE 2.6: Connected RCs

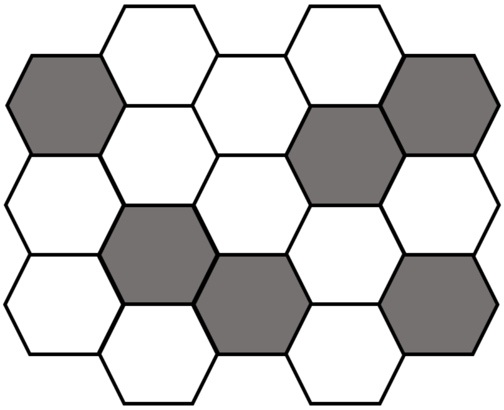


FIGURE 2.7: Scattered RCs

consider this set of reporting cells as a boundary, where all the call routing and call procedures are carried out. This is explained in detail in the section below.

2.4.2 Problem Formation

In RCP location management method, mobile terminals need to update their locations whenever they cross a reporting cell. During call arrival, users are located by paging in their last location updated reporting cell as well as its neighbouring non reporting cells without crossing another reporting cell. For example, in the reporting cell configuration shown in Fig 2.8 below, cells 3, 6, 9, 10, 11, 13 and 16 are reporting cells and the others are non-reporting cells. Let us say, an MT's location has been last updated in cell 3. Therefore, when there is a call arrival to that mobile terminal, paging is done in cells 1, 2, 3, 4, 5, 7, 8 and 12.

Location Management cost consists of location update cost and paging cost. Therefore, total cost of a given cellular network is equal to the sum of total number of location updates and total number of paging transactions over a certain period of time.

$$Total\ Location\ Cost = C * N_{LU} + N_P \tag{2.1}$$

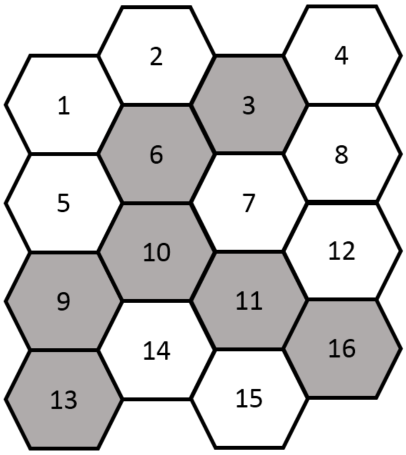


FIGURE 2.8: Example Reporting Cell Configuration

where, *C* is a positive constant which represents the cost ratio of location update to paging, and is taken as 10, i.e. *C*=10, because cost of location update is much higher than paging cost. N_{LU} is the total number of location updates and N_P is the total number of paging transactions in the given network. In a given cellular network, each cell i is associated with two weights: movement weight(w_{mi}) and call arrival weight (w_{ci}). w_{mi} represents the frequency (or total number) of movement of a MTs into a cell. w_{ci} represents the frequency of call arrivals in a cell. The total number of location updates and paging transactions in a network can be calculated using these two weights as follows:

$$N_{LU} = C * \sum_{i \in S} w_{mi} \tag{2.2}$$

$$N_P = \sum_{j=0}^{N} w_{ci} * v(j) \tag{2.3}$$

where N is the total number of cells in the network, S is the set of reporting cells and $v(j)$ is the vicinity value of cell j. Vicinity value is defined as the maximum number of cells that can be searched if an incoming call is received in cell j. Thus, Location management cost for a reporting cell configuration is obtained as:

$$Total\ Cost = C * \sum_{i \in S} w_{mi} + \sum_{j=0}^{N} w_{cj} * v(j) \tag{2.4}$$

$$Cost\ per\ Call\ Arrival = \frac{TotalCost}{\sum_{j=0}^{N} w_{cj}} \tag{2.5}$$

Movement and call weights are predefined. The objective is to minimize the cost per call arrival with a trade-off between update cost and paging cost and find the corresponding set of optimal reporting cell set.

CHAPTER 3

Optimization of Location Management Cost Using Evolutionary Computing Techniques

Optimization is a process of finding a best solution for a given problem. RCC is a discrete optimization problem, where the location management cost has to be minimized and the corresponding optimal set of reporting cells are to be determined. Genetic algorithm, binary particle swarm optimization and binary differential evolution algorithms are used to solve RCP problem. Each of these algorithms is discussed in detail below.

3.1 Genetic Algorithm

Genetic Algorithm (GA) is an adaptive heuristic search algorithm based on the biological evolutionary mechanism of natural selection and genetics. GA is an evolutionary algorithm which can find good, possibly optimal solutions, to optimization problems with huge state spaces to be searched. It is a global probabilistic search method. GA is inspired by Darwin's theory about evolution - "survival of the fittest".

Evolutionary Computing is a major research area in the field of artificial intelligence. Evolutionary algorithms use randomness and genetic inspired operations. These algorithms start with an initial potential solution set called as population. Each solution in the population is called as a chromosome or an individual. Each chromosome consists of a set of genes. In accordance with the problem statement, each RCC solution is a chromosome and individual cell is a gene. Major operations involved in evolutionary algorithms are selection, crossover, mutation and competition of the individuals in the population. The general evolutionary process is show in the figure below.

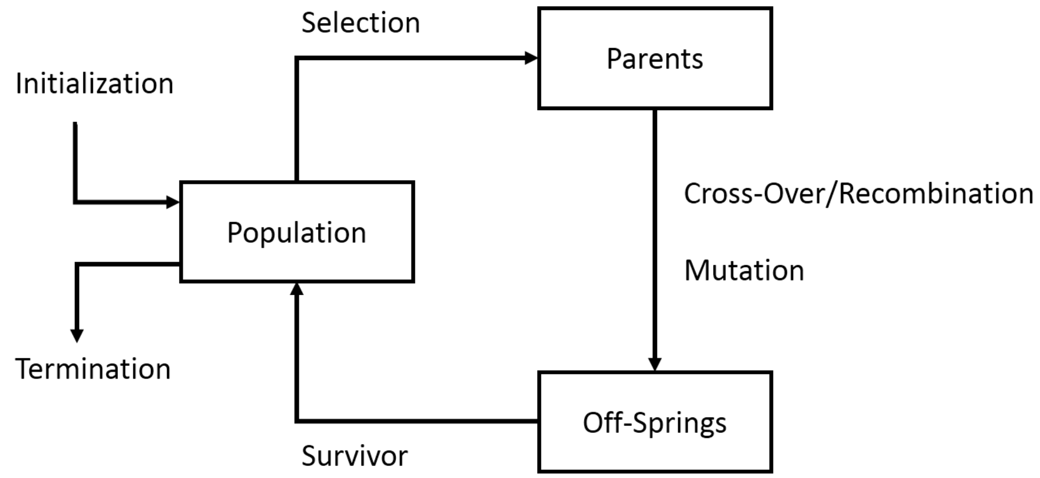


FIGURE 3.1: Evolutionary Process

3.1.1 GA Methodology

Objective/Fitness Function also called as fitness function, is the problem for which the best/optimal solution is to be found. Here, our objective function is the cost per call arrival function of reporting cell planning problem given by equation (2.5). Our goal is to minimize cost per call arrival and determine the optimal reporting cell set corresponding to minimum cost.

Search Space is the set of all possible solutions to the objective function. Each solution has a 'fitness' value given by the fitness/objective function. In our problem statement, for a cellular network containing N cells has a search space of 2N solutions. Each solution represents a reporting cell configuration which is a binary vector of size N. Each bit represents a cell. Bit value '1' refers to a reporting cell and '0' implies a non-reporting cell. Fitness value of a solution is cost per call arrival value of an RCC as given in equation (2.5). An example solution is shown below.

Cell Value	1	0	1	.	.	.	.	.
Cell number	1	2	3	.	.	.	.	N

FIGURE 3.2: Binary Solution Vector

Selection is the process of choosing individuals with a strong fitness value. Here we choose RCC solutions which have less cost value. Genetic algorithm start with an initial random population, say n solutions. Out of these solutions, we select two strong individuals randomly, called as parent individuals. The selection strategy used is Roulette Wheel Selection. This selection technique assigns a probability value to each solution based on its fitness. Stronger the individual, greater is the probability assigned. Since our problem is minimization function, RCC solution with lesser cost value will be assigned higher probability of selection.

Let us consider the individual RCC solution vector set as, $I = [I_1\ I_2 \ldots\ldots\ldots\ldots\ I_N]$. The corresponding location cost value vector of each solution is considered as, $f = [f_1\ f_2 \ldots\ldots\ldots\ldots\ f_N]$ Probability of selection of an RCC solution on roulette wheel is given by,

$$P(f) = \frac{f^{-1}}{\sum f} \tag{3.1}$$

A roulette wheel example is shown below.

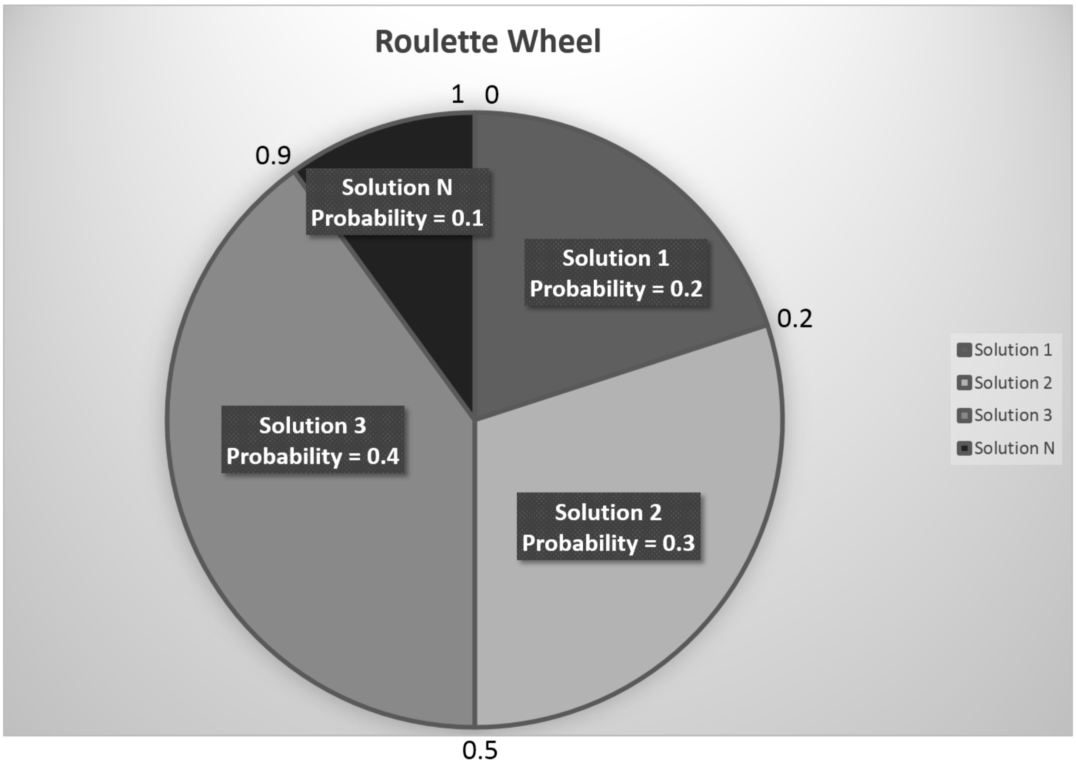


FIGURE 3.3: Example: Roulette Wheel

The wheel is rotated to selection a solution. A random number in the range [0,1] is generated. The solution corresponding to the probability slot which contains this random number will be selected.

Crossover combines the two parent individuals to form a new off-spring. Single point crossover is used in the algorithm here. It swaps a portion of the parent solution from a random point in the chromosomes and thus produces two new solutions.

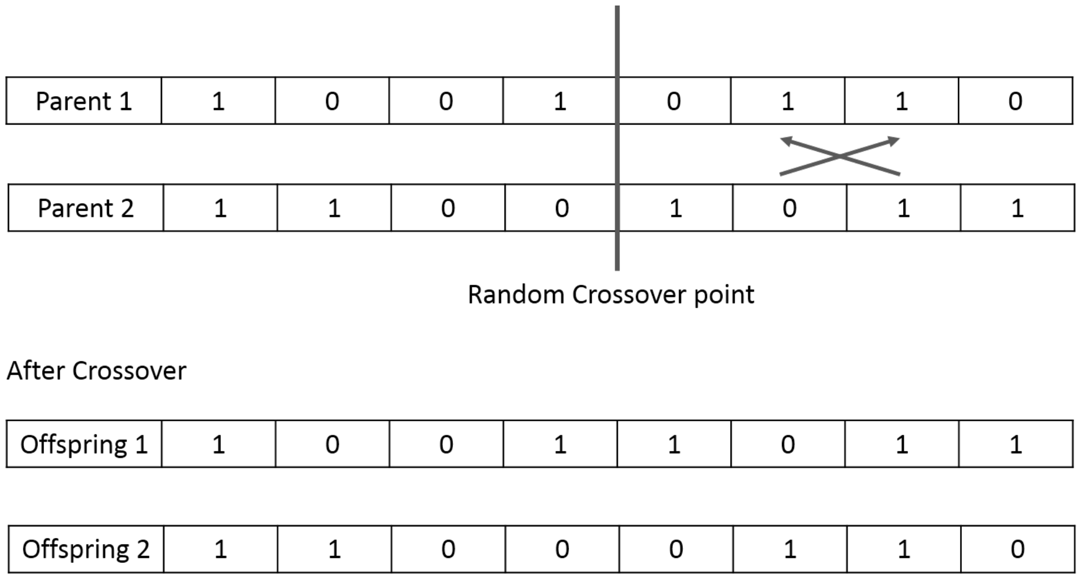


FIGURE 3.4: Example: Crossover Process

Mutation changes the value of a random gene in the chromosomes of the new off-springs produced after crossover. Changing the gene value refers to changing the value of a random bit in the new solutions produced, i.e. complement the bit value. An example of how mutation is done, is shown in the figure.

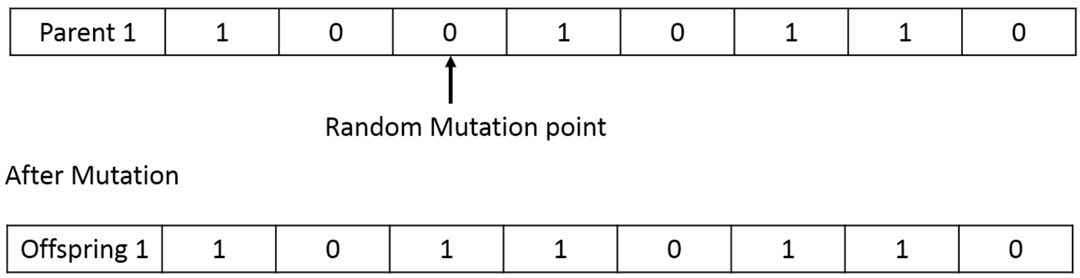


FIGURE 3.5: Example: Mutation

Survival The fitness of the new chromosomes thus produced are evaluated and compared with the fitness of the parent individual. Parent individuals are replaced with the off-springs if the fitness of parent individuals is weaker than the offspring's fitness.

The overall outline of the genetic algorithm implemented is presented in the section below.

3.1.2 Algorithm Outline for Cost Minimization

1. Random n number of RCC solutions are generated.

2. The total location management cost per call arrival of each RCC solution is evaluated.

3. New RCC solutions are created by repeating the following steps for n (number of solutions) times:

   - Selection - RCC solutions are selected using roulette wheel selection.
   - Crossover – Two RCC solutions are selected using roulette wheel and combined to form new RCC solutions.
   - Mutation - Mutation is performed if a random number generated is greater than the defined mutation probability. With a mutation probability, (taken as 0.8) the new solutions at random cell positions are mutated in the binary RCC solution vectors.

4. Updating the RCC solutions – If the cost of the new RCC solution is lesser than the cost of the previous RCC solution, the previous RCC solution is replaced with the new RCC solution.

5. If the end condition is satisfied i.e. maximum number of iterations, the process is terminated and the best RCC solution in the updated RCC solution vector set with the least cost value is returned.

6. Loop – The process is repeated from step 2.

The flow chart of genetic algorithm implemented for cost minimization is shown in the figure below.

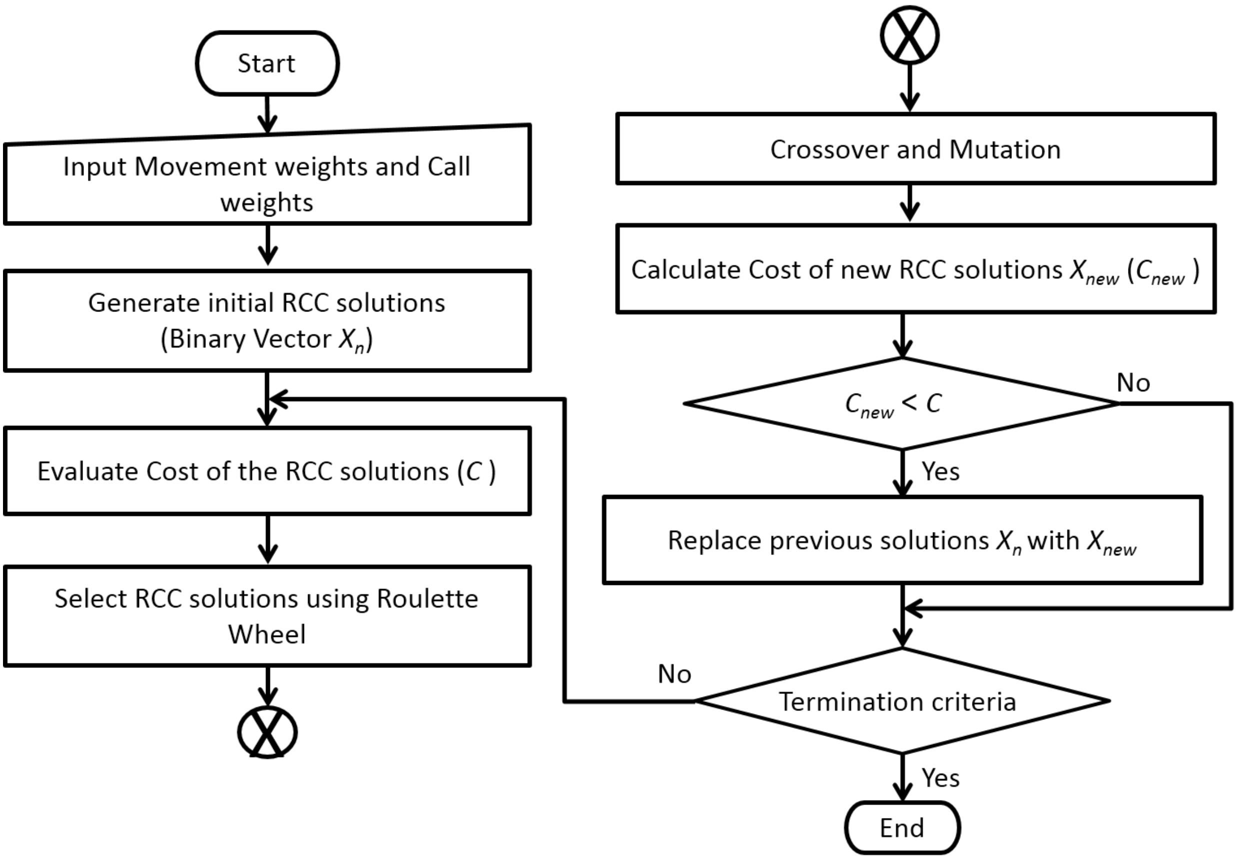
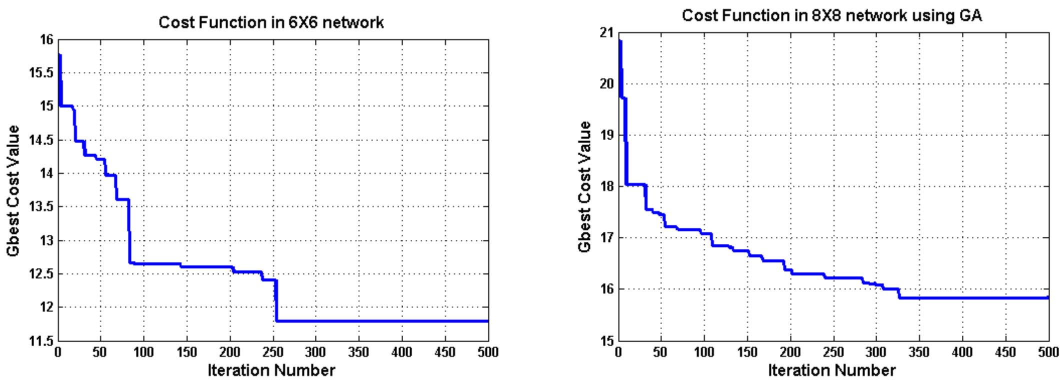


FIGURE 3.6: Genetic Algorithm Flow Chart

3.1.3 Cost Minimization Simulation using GA



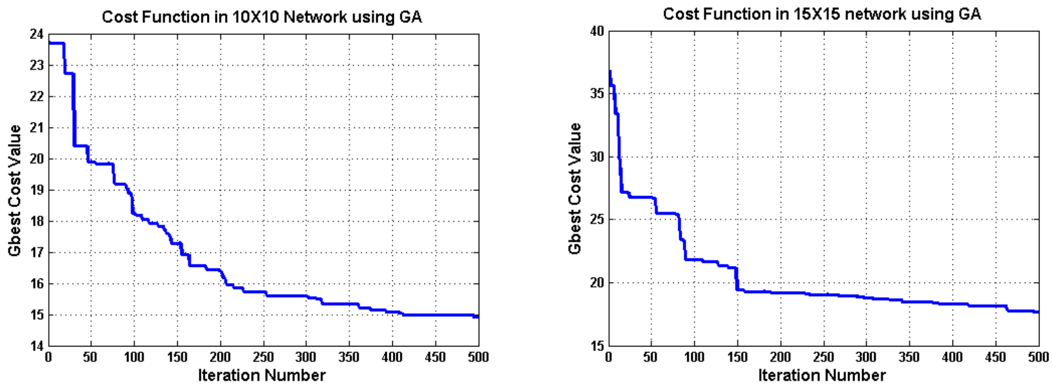


FIGURE 3.7: Cost Minimization using GA for Different Networks

Location management cost function behaviour using genetic algorithm for different test networks is shown in Fig 3.7. Equation (2.5) is optimized using GA for 6X6, 8X8, 10X10 and 15X15 test networks. Each simulation is run for 500 iterations. The minimum location cost value for every iteration is plotted against the iteration number. It is observed that the convergence of the cost function is fast in 6X6 network compared to other networks. Convergence of the cost function using GA reduces with the increase in network size. Also, it is observed that the percentage reduction in cost per call arrival, increases with the increase in network size.

3.2 Binary Particle Swarm Optimization

3.2.1 Introduction

Reporting Cell Planning (RCP) is a discrete optimization problem [16], where each RCC solution is represented as a binary vector of size N. Here, N is the size of the network. As discussed above, one represents a Reporting cell and zero represents a non-reporting cell. Therefore, all the cells in the network are either reporting or non-reporting cells. In this approach, we first generate random initial solutions of Reporting Cell Configuration(RCC). Cost per call arrival of all RCC solutions are evaluated using equation (2.5). The least cost achieved by an RCC solution in every iteration is denoted as $pbest$ (local best). The best RCC solution with least cost value achieved in the whole solution set is denoted as $gbest$ (global best). The best solution is the one that has minimum cost. The basic concept of Binary Particle Swarm Optimization lies in finding the best RCC solution, *gbest*, by using *pbest* of each RCC solution.

3.2.2 Algorithm Outline for Cost Minimization

1. In the first step, the number of solutions (i.e. n) to be taken and the number of iterations are given as input. Also, movement and call weights of each cell in the network are defined.

2. Initial n number of RCC solutions X i.e binary vectors of size N each, are generated. Each solution is represented as X_j^i i.e. j^{th} particle in iteration i.

3. The total location cost per call arrival of each solution is evaluated using equation (2.5), denoted as $f(X_j^i)$.

4. The vector probabilities of X, $pbest$ and $gbest$ are calculated as shown below:

$$P(X_j) = \frac{w \times \frac{1}{f(X_j)}}{w \times \frac{1}{f(X_j)} + c_1 \times \frac{1}{f(pbest_j)} + c_2 \times \frac{1}{f(gbest)}} \tag{3.2}$$

$$P(pbest_j) = \frac{c_1 \times \frac{1}{f(pbest_j)}}{w \times \frac{1}{f(X_j)} + c_1 \times \frac{1}{f(pbest_j)} + c_2 \times \frac{1}{f(gbest)}} \tag{3.3}$$

$$P(gbest) = \frac{c_2 \times \frac{1}{f(gbest)}}{w \times \frac{1}{f(X_j)} + c_1 \times \frac{1}{f(pbest_j)} + c_2 \times \frac{1}{f(gbest)}} \tag{3.4}$$

5. Using the vector probabilities obtained above, probability that each cell in the next solution is a reporting cell is calculated.

   If the cell value in X_i, $pbest_i$ and $gbest$ is zero, then the probability that it is a reporting cell in the next solution is also zero. If the cell value in X_i, $pbest_i$ and $gbest$ is one, then the probability that it is a reporting cell in the

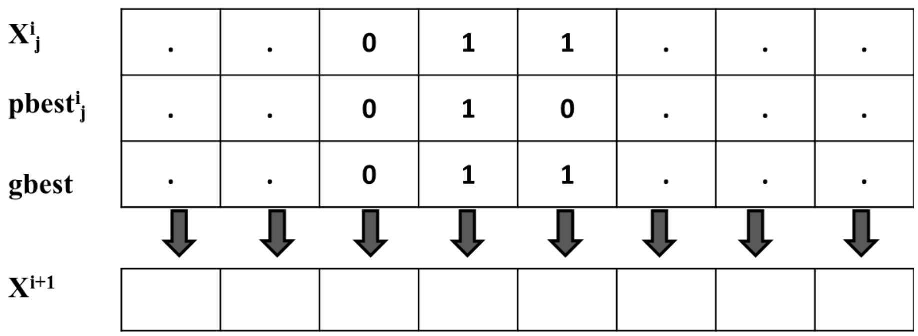


FIGURE 3.8: Generation of new RC configuration

next solution is one, else probability in the range (0,1) is obtained. Let the probability so obtained be represented as P_r.

6. Each cell probability P_r is then mapped to a range $[V_{min}, V_{max}]$. Here the range is [-4,4] so that each cell value has 0.018 probability to change. Mapping is done as:

$$P_m = P_r \times 8 - 4 \tag{3.5}$$

7. The probability of assigning a reporting cell to each cell in the next solution is calculated using Sigmoid function S.

$$S(P_m) = \frac{1}{1 + e^{-P_m}} \tag{3.6}$$

Each cell in the next solution is assigned a reporting cell as shown below:

$$X_j^{i+1} = \begin{cases} 0, & \text{if } rand() \geq S(P_m) \\ 1, & otherwise. \end{cases} \tag{3.7}$$

where *rand()* generates a random number between [0.0,1.0]. Thus, a new RCC solution set is obtained, denoted as X^{i+1}.

8. The location cost of the new RCC solutions X^{i+1} is evaluated and corresponding $pbest$ and $gbest$ are determined.

9. If the cost of j^{th} RCC solution in the new RCC solution set is less than the cost of j^{th} RCC solution in the previous RCC solution set, replace the

corresponding RCC solution in $pbest$ with the new RCC solution. If the cost of $gbest$ is less than the minimum of the cost of $pbest$ RCC solutions, replace $gbest$ RCC solution with the RCC solution corresponding to the minimum cost in $pbest$.

10. Continue this process from Step 4 for the desired number of iterations.

The solution obtained after the last iteration corresponding to $gbest$ gives the optimal set of reporting cells with the minimum location cost value.
The flow chart of BPSO is shown below.

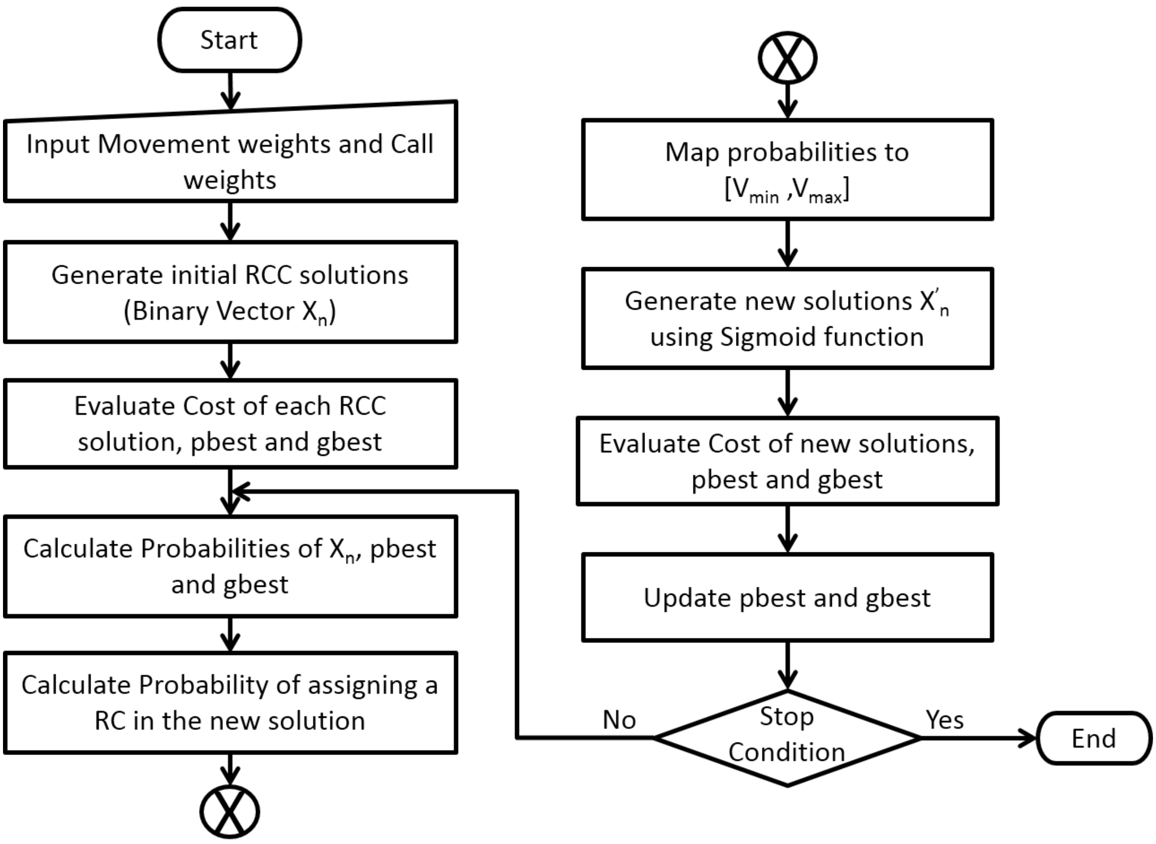


FIGURE 3.9: BPSO flow chart

3.2.3 Cost Minimization Simulation using BPSO

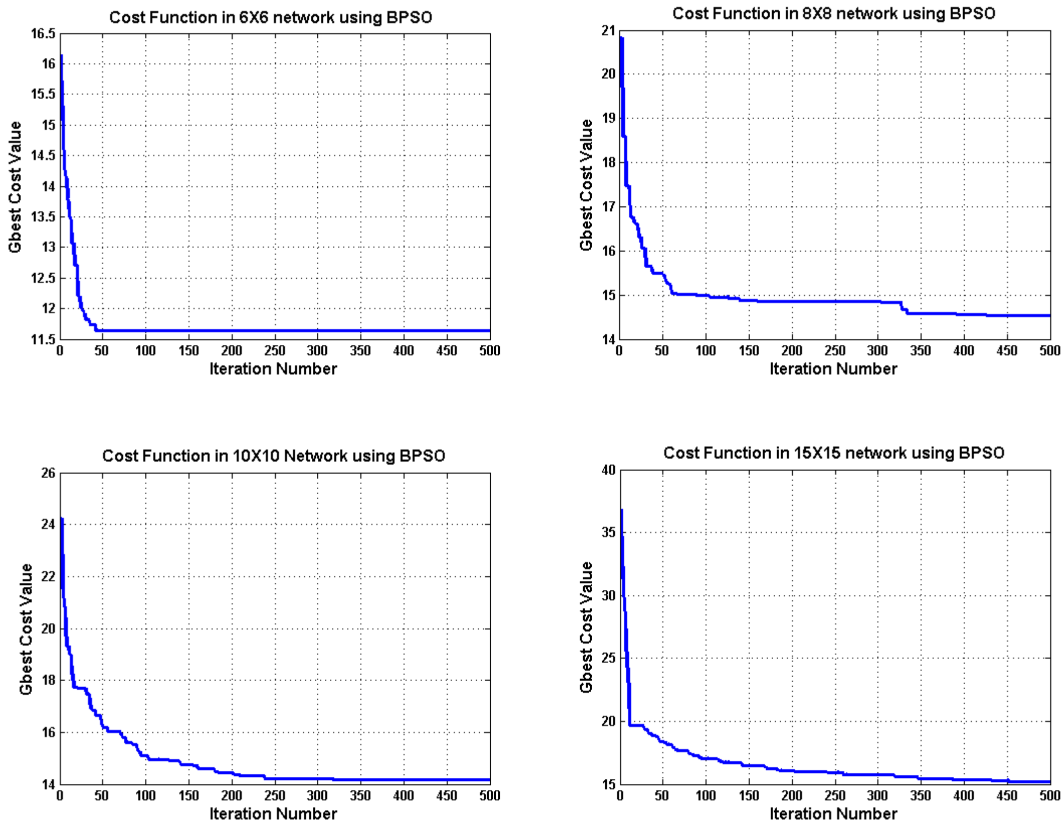


FIGURE 3.10: Cost Minimization using BPSO for Different Networks

Location management cost function behaviour using genetic algorithm for different test networks is shown in Fig 3.10. Equation (2.5) is optimized using BPSO for 6X6, 8X8, 10X10 and 15X15 test networks. Each simulation is run for 500 iterations. The minimum location cost value for every iteration is plotted against the iteration number. It is observed that the convergence of BPSO is fast in 6X6 network compared to other networks. Like in GA, it is observed that the percentage reduction in cost per call arrival, increases with the increase in network size. In the initial iterations the convergence of BPSO is fast and later it is observed that it slows down. This is attributed to the randomness of the solution in the initial iterations. After certain number of iterations, the RCC solutions tend to move towards the optimal RCC solution and hence convergence decreases.

3.3 Binary Differential Evolution

3.3.1 Introduction

Differential Evolution is a population-based evolutionary optimization technique, first proposed in 1995 by Price and Storn [17] . In this algorithm, solutions are randomly selected and their vector-difference is calculated. The vector-differences thus obtained are used to produce new solutions. Like in genetic algorithm, standard differential evolution also uses the three major operators i.e. mutation, crossover and selection operators. But the methodology of these operators in DE is different from GA (the methodology in GA). The drawback of this standard DE is that it works only in continuous space and is not suitable for binary optimization problems. Therefore we adopted Binary Differential Evolution algorithm for solving the Reporting Cell problem. In this Binary DE we use an additional operator called as probability estimation operator to generate new solutions [18] . The operators used in binary DE are discussed below in context of reporting cell planning.

3.3.2 Algorithm

Let us say, each Reporting cell configuration solution (also called as individual) as X_j, where *j* refers to j^{th} RCC solution. Thus X_j is a binary vector of length *N*, where *N* is the number of cells in the given cellular network. Initially, we generate *n* number of RCC solutions. Here X_{ij} denotes i_{th} cell (i.e. i_{th} bit) of j^{th} RCC solution in the solution set *X*.

Mutation There are many DE mutation schemes as given in [11] . Here we used DE/best/1/exp scheme i.e. Mutant vector = $X_{best} + F(x - y)$. In this binary space, mutant operator (MO) is calculated bit by bit and thereby mutant operator binary RCC vector is produced.

$$MO = X_{best} + F(x - y) \tag{3.8}$$

where X_best is the best RCC solution which corresponds to minimum location cost in the RCC solution set X. x and y are solutions selected randomly from RCC solution set X. F is a scaling factor which is a positive constant whose value lies in the range (0.2, 5).

Probability Estimation Operator (PEO)

This operator is used on the mutant vector as given by the equation given below.

$$PEO(X_{ij}) = \frac{1}{1 + e^{-2b(MO-0.5)/(1+2F)}} \tag{3.9}$$

where b is a positive real constant called as the bandwidth factor. This factor contributes to the shape and range of the probability distribution model. Here its value is fixed to be 20. The binary RCC vector obtained after probability estimation is called as probability estimation vector (PEV). Using this PEV and the target RCC solution (from RCC solution set X), binary mutant RCC individual (BMI) is generated according to the equation below.

$$BMI_{ij} = \begin{cases} 1, & \text{if } rand() \leq PEV(X_{ij}) \\ 0, & otherwise. \end{cases} \tag{3.10}$$

Crossover Operator

Crossover operator produces trial RCC solutions T_j by combining mutant RCC vector BMI_j and target RCC solution X_j. The trial RCC solution vectors are produced using the following equation.

$$T_{ij} = \begin{cases} BMI_{ij}, & \text{if } rand() \leq C_r \text{ or } randi() = i \\ X_{ij}, & otherwise. \end{cases} \tag{3.11}$$

where C_r is the crossover probability taken as 0.15. It lies in the range of [0.1,0.3]. The function $randi()$ generates an integer in the range [1,N].

Selection Operator

Selection operator determines if the trial RCC solution is better than the target RCC solution i.e the current RCC solution. If the location cost value of the trial RCC solution T_j is less than the location cost of the current RCC solution X_j , then X_j is replaced with T_j.

$$X_{j(new)} = \begin{cases} T_j, & \text{if } Cost(T_j) \leq Cost(X_j) \\ X_j, & otherwise. \end{cases} \tag{3.12}$$

where X_{new} is the new RCC solution set.

In brief, the binary differential evolution algorithm is explained as:

1. Initial RCC solutions are randomly generated.
2. The required control parameters i.e. maximum number of iterations, scaling factor F, bandwidth factor b and crossover probability C_r are initialized.
3. The cost of the initial random RCC solutions is evaluated and the RCC solution with minimum location cost is determined, denoted as g_{best} (global best).
4. Binary mutant RCC vectors are generated using mutation operator and probability estimation operator.
5. Trial RCC vectors are generated using crossover operator.
6. Using selection operator, new set of RCC solutions is determined.
7. The location cost of the new RCC solution set is evaluated. The new g_{best} RCC solution in the new solution set is determined and the previous g_{best} RCC solution is replaced with the new g_{best} RCC solution.

8. The process is repeated from step 4 until the termination criterion is met.

The flow chart of binary differential evolution algorithm is shown in the figure below.

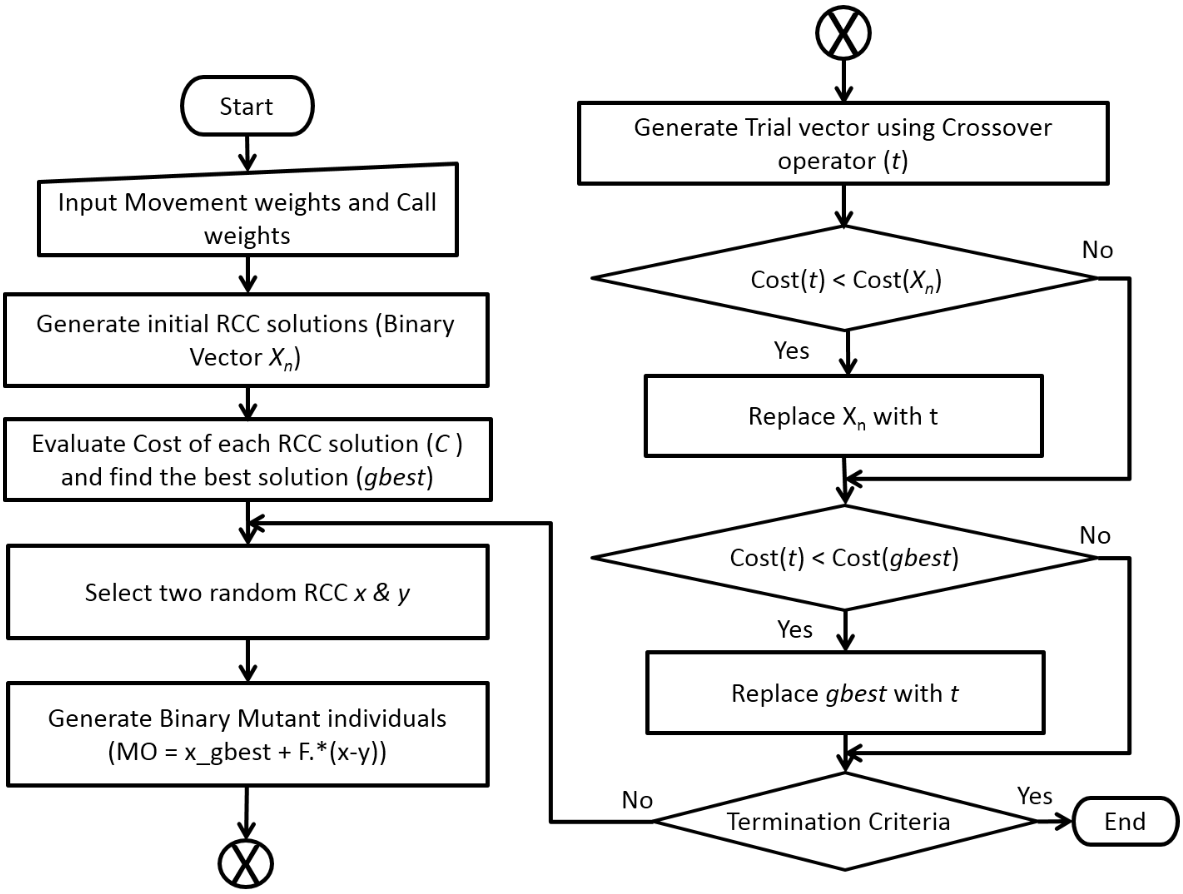


FIGURE 3.11: Binary Differential Evolution Flow Chart

3.3.3 Cost Minimization Simulation using BDE

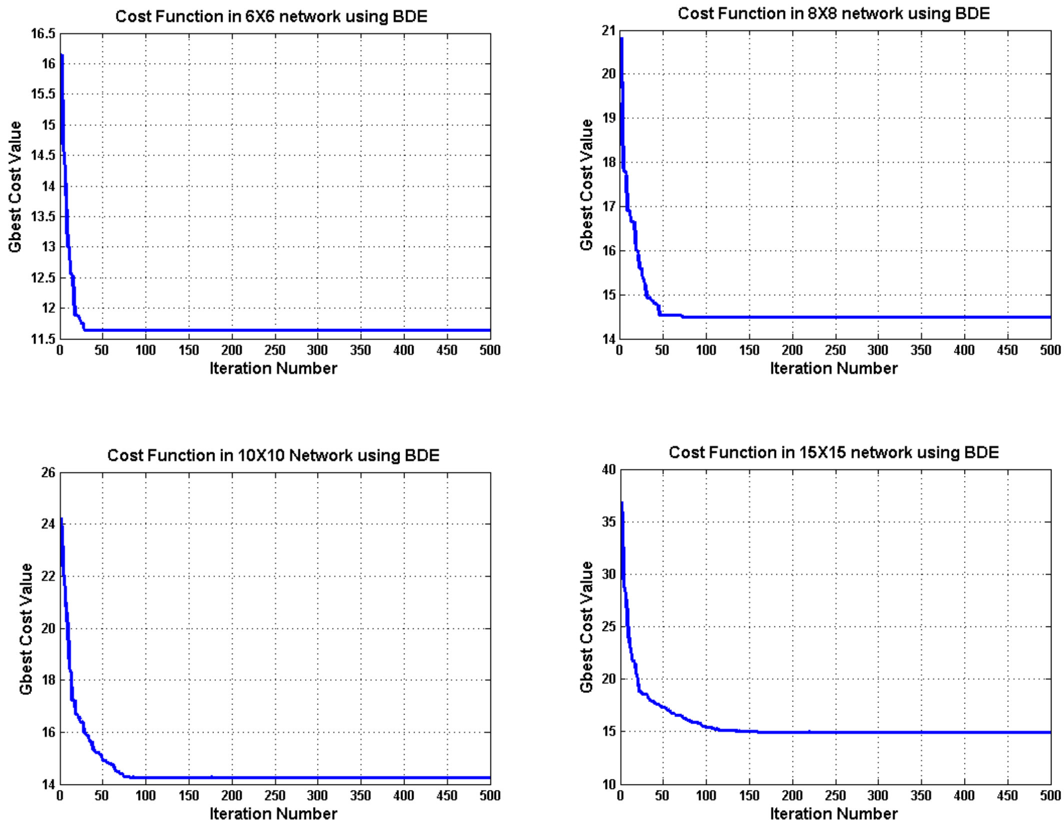


FIGURE 3.12: Cost Minimization using BDE for Different Networks

Location management cost function behaviour using genetic algorithm for different test networks is shown in Fig 3.12. Equation (2.5) is optimized using BDE for 6X6, 8X8, 10X10 and 15X15 test networks. Each simulation is run for 500 iterations. The minimum location cost value for every iteration is plotted against the iteration number. Cost function behaviour to BDE is observed to be similar to the behaviour of BPSO. A comparative study of the results obtained using different algorithms is required to analyse the algorithms and their behaviour.

CHAPTER 4

Comparative Study of the Implementation Strategies

Test networks 6x6, 8x8, 10x10 and 15x15 are used for implementing the reporting cell planning and their cost function behaviour to different optimization algorithms is shown in the figures below. Simulations were executed in MATLAB. The simulation results show the plot of overall best reporting cell configuration cost in each iteration. Each simulation is run for 500 iterations. For each of the three algorithms used, minimum location cost achieved in every iteration is plotted against total number of iterations.

4.1 Result Analysis

In all the results shown in Fig 4.1, GA seems to be a weak algorithm for the discrete location cost optimization problem. It is observed that the optimum cost value is the same in BPSO and BDE, for smaller networks such as 6X6 network. As the network size increases, BDE gives the best optimum results compared to BPSO and GA. Average standard deviation of BPSO increases with the the network size. The convergence of BDE is observed to be faster than GA and BPSO.

Simulation results are shown below:

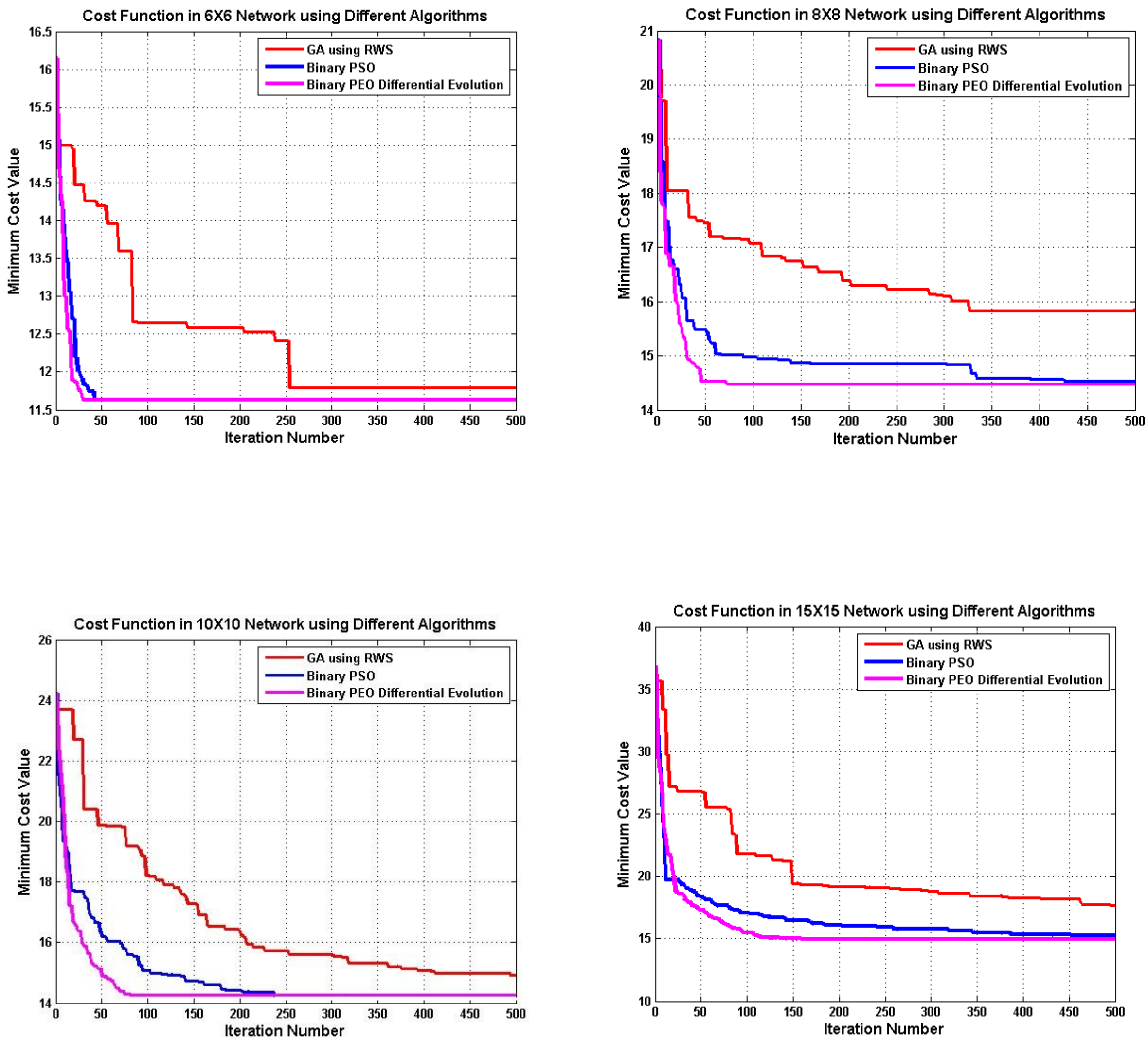


FIGURE 4.1: Cost Minimization in Different Networks for Different Algorithms

BDE consumes the least computation time and GA consumes the maximum computation time. The computation time taken by GA is four the computation time of BDE. The computation time taken by BPSO is 2 times the computation time of BDE. The convergence of BDE and BPSO is faster than GA. BDE has comparatively faster convergence than BPSO. The table below gives a comparison of the optimized reporting cell planning location cost, with the algorithms implemented and algorithms previously implemented by other researchers.

Box plots showing minimum cost values for different algorithms

The boxes in figure 4.2 corresponds to 50% of the best cost values within 1.5 standard deviation, obtained for every iteration of the algorithms. The vertical lines called whiskers, extending above and below the boxes are variabilities and '+' symbol shows the outliers of the sequence. The horizontal line in each box denotes the median of that sequence. Box plot gives the spread of the best cost values. Below shown are box plots for the four test networks against the three optimization techniques used.

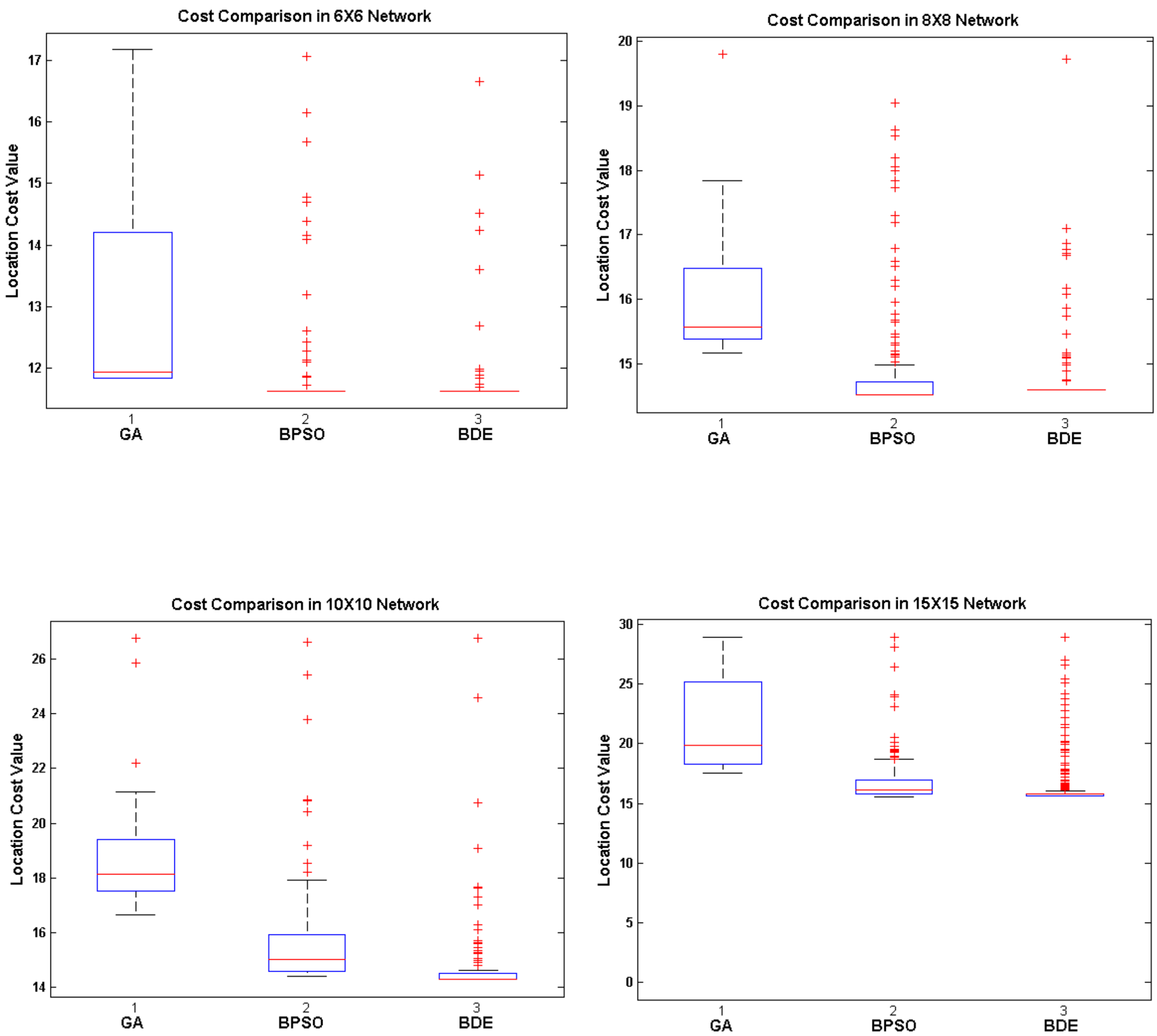


FIGURE 4.2: Minimum Cost Values in different networks for different algorithms

It is observed from figure 4.2 that, BDE has the least median cost value and GA has the highest median cost value. Also, the cost values in GA are scattered over a comparatively large range than BPSO and BDE, which implies that rate at which it converges is slow. At the same time, cost values in BDE are spread in close vicinity to the median value unlike the other algorithms. This implies that the BDE converges fast towards the optimum value. BPSO shows an intermediate behaviour compared to GA and BDE.

Cost Comparison

TABLE 4.1: Minimum Cost Comparison in Different Networks Using Various Algorithms

Network	BDE	BPSO	GA	ACO	TS	MHN
6X6 (36 cells)	11.522	11.522	11.787	11.522	11.522	11.522
8X8 (64 cells)	14.513	14.725	14.831	14.725	14.725	N/A
10X10 (100 cells)	14.035	14.317	15.992	N/A	N/A	15.785
15X15 (225 cells)	14.967	15.223	17.695	N/A	N/A	N/A

It can be concluded from the table and the results obtained, that BDE gives best results for reporting cell planning location management optimization problem. It shows superior performance in terms of convergence, optimum result and computation time.

Optimal Reporting Cell Configuration of the Test Networks

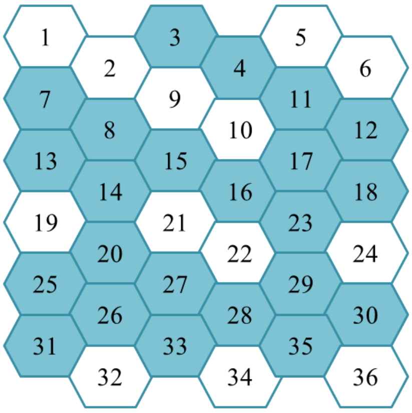


FIGURE 4.3: Optimum RCP in 6X6 test network

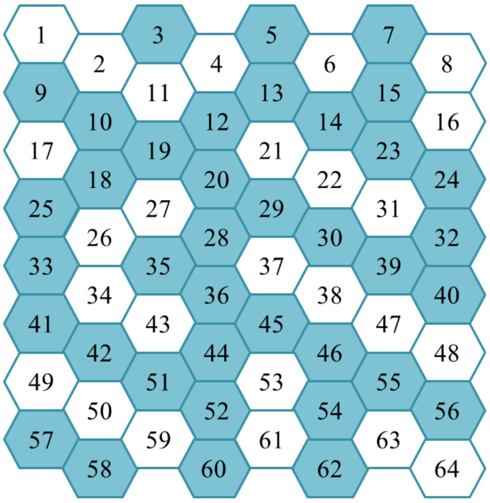


FIGURE 4.4: Optimum RCP in 8X8 test network

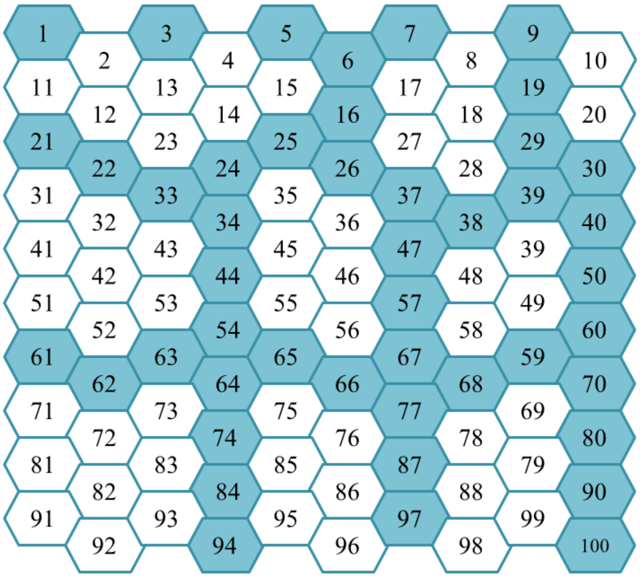


FIGURE 4.5: Optimal RCP in 10X10 test network

The figures above show the optimum reporting cell planning in different test networks. These configurations contribute to minimum location management cost obtained using binary differential evolution.

CHAPTER 5

Conclusions and Future Scope

- The location management optimization problem has been generalized for any size N of a cellular network.
- Genetic algorithm, binary particle swarm optimization and binary differential evolution optimization techniques have been used to minimize the location cost and to determine the optimal reporting cell set in a given cellular network of size N.
- To the best of our knowledge, binary differential evolution has been implemented for the first time to optimize location management cost in reporting cell planning.
- Various parameters involved with the implemented algorithms have been analysed and fine-tuned to obtain optimal results.
- Further, the reference data set has been validated with BSNL data and the cost function has been optimized.

As observed from the simulation results, binary differential evolution outperforms other algorithms that have been used and compared with. Binary differential evolution gives the best results compared with the other optimization techniques used. Location management cost has been minimized and the corresponding optimum reporting cell configuration for a given network is determined.

Future Scope

Future work includes hybridization with other optimization techniques as well as more detailed and in depth comparison with other search algorithms. Consequently, dynamic location management is the current challenging issue. As the number of subscribers is increasing day by day, and transitions occurring from 2G to 3G and beyond, location management should be efficiently carried out to improve the total location cost, while allocating appropriate reporting cells in a practical, real-time implementable fashion.

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